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Computer Vision-Based Plastic Waste Detection and Weight Estimation

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Abstract

Plastic waste management is an increasingly critical environmental challenge due to the growing volume of waste and the limitations of conventional manual weighing methods, which are inefficient and prone to human error. This study proposes a computer vision-based system for automatic detection, classification, and weight estimation of plastic waste using the YOLOv8n model for object detection and Random Forest Regression for weight estimation. The YOLOv8n model is used to detect and classify seven types of plastic waste based on the Resin Identification Code (RIC), namely PET, HDPE, PVC, LDPE, PP, PS, and OTHER. Subsequently, weight estimation is performed using a Random Forest Regression model based on bounding box features, including width, height, area, aspect ratio, and perimeter. The proposed system is evaluated using an unseen test set to ensure unbiased performance measurement. Experimental results show that the YOLOv8n model achieves a mean Average Precision (mAP@0.5) of 91.93% and mAP@0.5:0.95 of 73.27%, while the Random Forest Regression model achieves an R^2 score of 95.5% with a Mean Absolute Error (MAE) of 4.28 grams. These results demonstrate that the integration of object detection and regression enables accurate and automatic estimation of plastic waste weight under controlled image acquisition conditions, thereby improving the efficiency and objectivity of waste management systems.

Keywords— *computer vision, plastic waste detection, YOLOv8n, weight estimation, Random Forest Regression*

1. Introduction

The rapid development of Artificial Intelligence (AI) and computer vision over the past decade has significantly advanced digital image processing, particularly in object detection and quantitative analysis based on visual information (Harahap & Muliantara, 2024; Jiao et al., 2020). Computer vision enables systems to automatically extract, model, and interpret information from images and videos, making it widely applicable in object recognition, image classification, and various forms of data-driven visual estimation (Nugroho et al., 2026). Among various real-time object detection approaches, the You Only Look Once (YOLO) family of algorithms has become one of the most widely used methods due to its ability to perform simultaneous detection and classification of multiple objects within a single image with high computational efficiency (Mahardhika & Pakereng, 2026; Santiago et al., 2024).

In the environmental context, plastic waste has become an increasingly urgent global issue (Larasati et al., 2024). According to the Ministry of Environment and Forestry (KLHK), Indonesia generates more than 38 million tons of waste annually, with plastic waste contributing approximately 16–20% of the total waste volume (Annatasya et al., 2024; *SIPSN - Sistem Informasi Pengelolaan Sampah Nasional*, n.d.). This indicates that plastic waste is one of the dominant components in the national waste management system, requiring more effective and measurable handling approaches. Furthermore, the World Economic Forum reports that the life cycle of plastic waste contributes to global carbon emissions exceeding 850 million tons of CO_2 annually, highlighting the need for more accurate measurement approaches to support environmental policies and climate change mitigation efforts (Cottom et al., 2024).

One of the critical aspects of plastic waste management is weight measurement, which is used for recycling analysis, waste management evaluation, and environmental impact assessment (Heinonen, 2021; Salamah et al., 2023). However, in practice, weight estimation is still predominantly performed manually using conventional weighing scales. This approach has several limitations, including inefficiency, dependency on human operators, and potential measurement errors, particularly in field conditions involving large volumes and diverse types of waste (Hendradi et al., 2025). Therefore, an automated system capable of identifying and estimating plastic waste weight more quickly, accurately, and consistently is required (Dongre et al., 2026).

Previous studies have extensively developed computer vision-based systems for plastic waste detection and classification using deep learning methods (Shukhratov et al., 2024; Sihananto et al., 2022). However, most of these studies focus only on object identification without performing automatic quantitative estimation such as weight prediction (Kroell et al., 2021). In addition, geometric information obtained from object detection, such as bounding box dimensions, has not been optimally utilized as features for quantitative prediction. This highlights a research gap that can be further explored to develop a system that not only recognizes plastic waste types but also estimates their weight based on visual information (Faizal et al., 2023; Firdaus et al., 2025; Islam et al., 2026).

Based on these problems, this study proposes the development of a computer vision-based system for detecting and classifying plastic waste types while simultaneously estimating their weight from digital images (Kunwar et al., 2024; Tran & Nguyen, 2025). The system uses the YOLOv8n model to detect seven types of plastic waste based on the Resin Identification Code (RIC), namely PET, HDPE, PVC, LDPE, PP, PS, and OTHER (Hakim, 2025). Subsequently, visual features extracted from bounding box results, such as width, height, area, aspect ratio, and perimeter, are used as input to a Random Forest Regression model for automatic weight estimation of plastic waste (Almira et al., 2024; Moghaddam et al., 2024).

This approach enables image-based weight estimation by utilizing visual features extracted from detected plastic objects, thereby improving efficiency, consistency, and objectivity in plastic waste management. The integration of YOLOv8-based object detection and machine learning-based regression contributes to the development of an intelligent system that combines visual analysis and quantitative prediction. This study aims to develop a system capable of accurately detecting, classifying, and estimating plastic waste weight, while also supporting the digital transformation of waste management through artificial intelligence technology.

2. Method

This study employs the Design Science Research (DSR) approach with quantitative experimental evaluation. The DSR approach is used because this research focuses on the design and development of an artifact in the form of a computer vision-based system for automatic detection, classification, and weight estimation of plastic waste (Adjie & Zakaria, 2026). Quantitative experimental evaluation is applied to measure system performance based on numerical metrics in both object detection and weight estimation processes (Delport et al., 2024; Premananda et al., 2022).

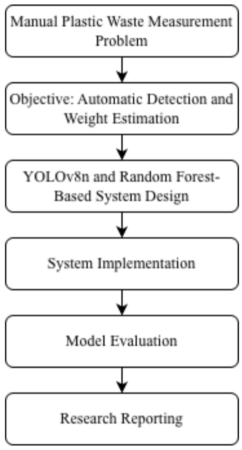

Figure 1. Design Science Research workflow.

The developed system consists of two main models, namely YOLOv8n for plastic waste detection and classification, and Random Forest Regression for weight estimation. YOLOv8n is used to detect seven types of plastic waste based on the Resin Identification Code (RIC) categories, namely PET, HDPE, PVC, LDPE, PP, PS, and OTHER. The detection results in the form of bounding boxes are then used to extract visual features, including width, height, area, aspect ratio, perimeter, and class ID. These features are used as inputs to the Random Forest Regression model to predict the weight of plastic waste in grams.

2.1 Dataset and Preprocessing

The dataset used in this study consists of two parts, namely an object detection dataset and a weight estimation dataset. The object detection dataset consists of 2,753 images with a total of 3,805 plastic waste objects annotated in YOLO format. Each object is classified into seven classes, namely PET, HDPE, PVC, LDPE, PP, PS, and OTHER.

In this study, the definition of a single object refers to an individual plastic component that has a specific plastic material type and an independently measurable weight value. A plastic product consisting of multiple components with different plastic types is considered as multiple objects. For example, a plastic bottle body made from PET and a bottle cap made from PP are annotated as two separate objects because each component has different material characteristics and weight values. Meanwhile, components with the same plastic material type that belong to the same physical unit are considered as one object, while physically separated plastic items are considered as different objects even if they have the same material type.

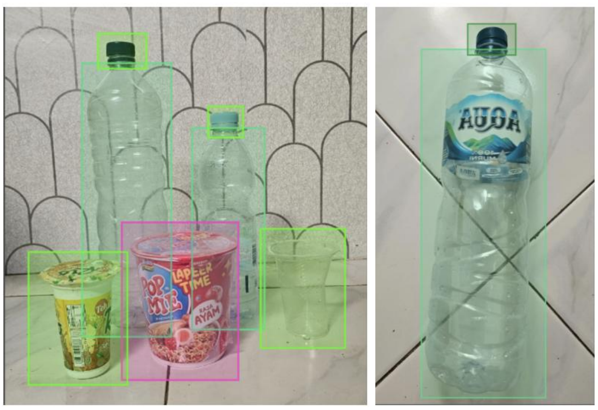

Figure 2. YOLO-annotated plastic waste components with individual bounding boxes.

The dataset is divided using a stratified sampling method into three subsets, namely training data (70%), validation data (15%), and testing data (15%), to ensure balanced class distribution and to avoid data leakage during the model evaluation process. Consequently, the final evaluation is performed on completely unseen test data to obtain objective results.

The weight estimation dataset consists of 700 samples containing object class information, geometric features extracted from bounding boxes, and actual plastic waste weight in grams as the ground truth. The image acquisition process was conducted under controlled conditions to maintain consistency between visual features and physical weight measurements. The camera position, distance, viewing angle, resolution, and lighting conditions were kept relatively constant during data collection. Therefore, the extracted bounding box features represent the object scale within a consistent imaging environment rather than absolute physical dimensions. No external scale reference object or camera calibration procedure was applied in this study because the model was developed and evaluated under a fixed image acquisition setup. The features used include width, height, area, aspect ratio, perimeter, and class ID, which are obtained from the detection results of the YOLOv8n model.

Table 1. Dataset for plastic waste weight estimation.

Filename	Class	Class ID	Confidence	BBox (X,Y)	Width	Height	Area	Weight (g)
hdpe_058.jpg	HDPE	1	0.864	(362, 428)	363	254	92276	55.3
ps_000.jpg	PS	5	0.920	(196, 58)	361	277	100000	43.7
ldpe_096.jpg	LDPE	3	0.890	(235, 333)	235	176	41446	10.9
hdpe_055.jpg	HDPE	1	0.957	(110, 335)	258	130	33605	28.1
ldpe_021.jpg	LDPE	3	0.950	(333, 102)	380	210	80000	26.5

The preprocessing stage is performed by resizing the images to 640 × 640 pixels using the letterbox method to preserve the image aspect ratio. In addition, bounding box annotation validation is conducted to ensure the consistency between labels and objects within the images. To increase dataset variability, data augmentation techniques are applied, including scaling, translation, color adjustment, horizontal flipping, and mosaic augmentation.

2.2 YOLOv8n Model Training

The YOLOv8n model is used to detect and classify plastic waste objects into seven categories, namely PET, HDPE, PVC, LDPE, PP, PS, and OTHER. The model input consists of images with a size of 640 × 640 pixels, while the output includes class labels, confidence scores, and bounding box coordinates. The training process is conducted for 50 epochs with a batch size of 4 using the AdamW optimizer.

Object detection evaluation is performed using the Intersection over Union (IoU) metric, which measures the overlap between the predicted bounding box and the ground truth bounding box (Pardede & Hardiansah, 2022; Rezatofighi et al., 2019), defined as follows:

$$IoU = \frac{B_{pred} \cap B_{gt}}{B_{pred} \cup B_{gt}} \quad (1)$$

In addition, the YOLOv8 loss function consists of a combination of several components, namely bounding box loss, classification loss, and distribution focal loss (Fitriyono et al., 2025), which can be formulated as:

$$Loss = L_{box} + L_{cls} + L_{dfl} \quad (2)$$

2.3 Weight Estimation Using Random Forest Regression

Plastic waste weight estimation is performed using the Random Forest Regression model, an ensemble learning method that constructs multiple decision trees and combines their outputs to produce more stable and accurate predictions (Wen & Yang, 2021). This model is selected due to its ability to handle non-linear relationships between visual features extracted from detection results and actual weight values (Maulana et al., 2025).

In this study, the model input consists of features extracted from YOLOv8n bounding box detection results, namely width, height, area, aspect ratio, perimeter, and class ID. Meanwhile, the target output is the actual weight of each individual plastic object in grams, obtained through direct measurement using a digital scale as the ground truth. Each plastic component was weighed separately according to its object definition. The measurement was performed before image acquisition to ensure that each ground truth value corresponded to the annotated object. Therefore, components such as bottle bodies and bottle caps are assigned separate weight values when they belong to different plastic material categories.

Formally, the Random Forest prediction can be expressed as an aggregation of N decision trees as follows:

$$\hat{y} = \frac{1}{N} \sum_{i=1}^{n} f_i(x) \tag{3}$$

where $\hat{y}$ represents the predicted weight, N is the number of decision trees, $f_i(x)$ is the prediction of the i-th tree, and x is the feature vector extracted from the bounding box.

This ensemble approach allows the model to reduce variance and improve generalization to unseen data, making it suitable for weight estimation based on visual features extracted from images.

2.4 System Workflow

The system workflow is designed as a computer vision-based pipeline that integrates object detection and automatic plastic waste weight estimation. The system operates in an end-to-end manner, starting from image input and producing outputs in the form of plastic waste type and estimated weight.

The process begins with an input image of plastic waste obtained either through a camera or image upload. The image is then processed by the YOLOv8n model to perform both object detection and classification of plastic waste types. The output of this stage includes bounding boxes, object classes, and confidence scores for each detected object.

Next, the bounding box information is used in the feature extraction stage, where geometric features representing object characteristics in the image are computed. The extracted features include width, height, area, aspect ratio, and perimeter. These features are then used as input to the Random Forest Regression model to estimate the weight of each detected plastic waste object.

The final stage involves aggregating the prediction results to produce the system output, which includes detected plastic types, number of objects, estimated weight per object, and total plastic waste weight in a single image. Since each detected object represents an independently measurable plastic component, the total weight is calculated by summing the predicted weights of all detected objects. Duplicate detections of the same physical component are avoided through the YOLO confidence filtering and non-maximum suppression mechanism during object detection. Therefore, different components such as PET bottle bodies and PP caps are intentionally included as separate weight contributions. The system workflow is illustrated in Figure 3.

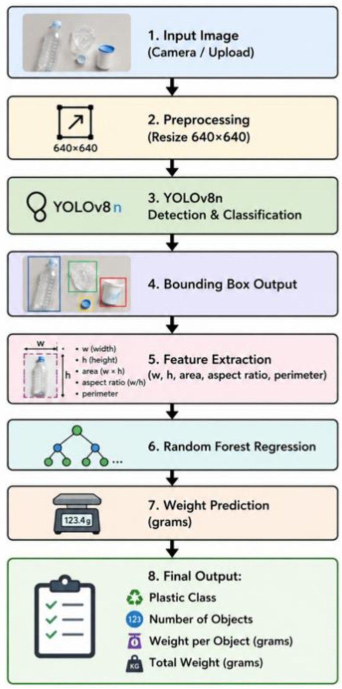

Figure 3. System workflow of plastic waste detection and weight estimation.

2.5 Model Evaluation

Evaluation is conducted to measure the performance of the system on two main components, namely object detection and weight estimation. The dataset was divided into training, validation, and test sets using a stratified sampling approach. The YOLOv8n model is evaluated using precision, recall, mAP@0.5, and mAP@0.5:0.95 metrics to assess the accuracy of plastic waste detection and classification. Precision and recall are used to measure the correctness and completeness of detections, while mAP is used to evaluate the overall model performance across different Intersection over Union (IoU) thresholds (Dharmasaputra & Hartato, 2025). The evaluation of YOLOv8n was conducted on an unseen test set to ensure unbiased performance measurement.

Meanwhile, the Random Forest Regression model is evaluated using R^2 Score, Mean Absolute Error (MAE), and Mean Squared Error (MSE). R^2 is used to measure how well the model explains the variance in the actual data, while MAE and MSE are used to measure prediction error. A higher R^2 value and lower MAE and MSE values indicate better model performance in weight estimation (Winardi et al., 2026).

3. Results And Discussion

3.1 Object Detection Performance (YOLOv8n)

The experimental results of the YOLOv8n model demonstrate that the system is capable of effectively detecting and classifying plastic waste into seven classes, namely PET, HDPE, PVC, LDPE, PP, PS, and OTHER. The model was evaluated using a test set that was not used during the training process (unseen data) to assess its generalization ability under various image conditions, including variations in object size, position, and background complexity.

Quantitatively, the YOLOv8n model achieved a mAP@0.5 of 91.93% and a mAP@0.5:0.95 of 73.27%, indicating good and stable detection performance on previously unseen data. These results suggest that the model is capable of accurately localizing objects while maintaining performance across different Intersection over Union (IoU) thresholds.

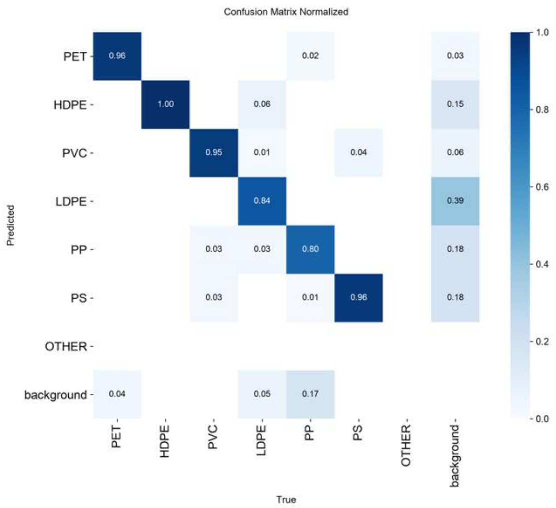

Figure 4. Confusion matrix of YOLOv8n detection results on the test dataset.

Figure 4 presents the confusion matrix of the YOLOv8n model on the test dataset, which generally shows good classification performance across most plastic waste categories. The PET and HDPE classes achieve the highest performance, with values of 0.96 and 1.00, respectively, while the PVC class also shows stable performance with a value of 0.95. However, performance degradation is observed in the LDPE and PP classes, with values of 0.84 and 0.80, as well as misclassifications into the background class, particularly for PP (0.18) and LDPE (0.17), indicating the presence of false negatives under certain conditions. Overall, these results indicate that the model performs well, although challenges remain for classes with similar visual characteristics and less clear object conditions.

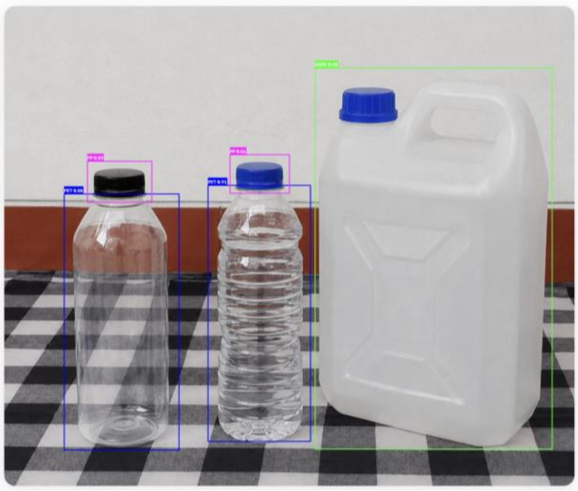

Figure 5. Detection results using YOLOv8n (bounding box visualization)

The model is capable of detecting multiple objects within a single image while providing bounding boxes and class labels with high confidence scores. In this case, different plastic components within the same product can be detected as separate objects when they have different plastic type categories. For example, a bottle body and its cap are treated as independent objects because they have different plastic types and weight ground truths. These results demonstrate that the model has stable multi-object detection capability under the evaluated image acquisition conditions.

Overall, the strong performance is attributed to the efficient multi-scale feature extraction capability of the YOLOv8n architecture, as well as the use of data augmentation techniques during training, which improve the model's generalization ability.

3.2 Weight Estimation Performance (Random Forest Regression)

The Random Forest Regression model is used to estimate plastic waste weight based on geometric features obtained from YOLOv8n detection results. The evaluation is conducted using several regression metrics to measure prediction accuracy and stability. The experimental results show that the model achieves an R^2 score of 95.5%, a Mean Absolute Error (MAE) of 4.28 grams, and a Mean Squared Error (MSE) of 37.02 g^2. These results indicate that the model is capable of effectively learning the relationship between bounding box features (width, height, area, aspect ratio, and perimeter) and the actual weight. The high R^2 value demonstrates that most of the variance in the data is explained by the model, while the low error values (MAE and MSE) indicate that the predictions are accurate and stable.

Table 2. Regression evaluation results.

Metric	Value	Formula	Purpose
R^2 Score	95.5%	$1 = \frac{SS_{res}}{SS_{tot}}$	Variance explained (0-100%, higher better)
MAE	4.28 g	$\frac{1}{n}\sum \lvert y_i - \hat{y}_i \rvert$	Average error magnitude
MSE	37.02 g^2	$\frac{1}{n}\sum (y_i - \hat{y}_i)^2$	Squared error (penalizes large errors)

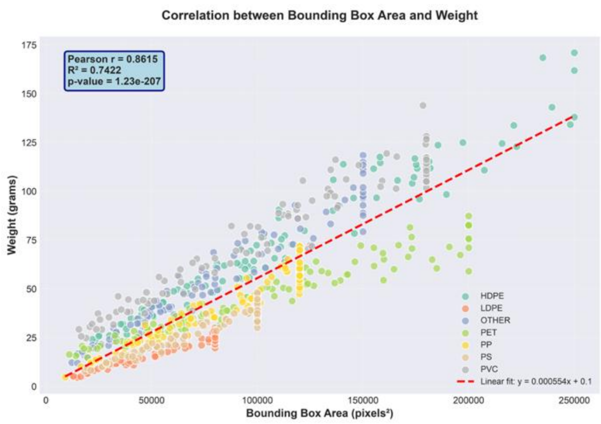

Figure 6. Correlation between bounding box area and weight.

3.3 End-to-End System Performance

The experimental results show that the integration of the YOLOv8n model and Random Forest Regression is capable of producing an end-to-end system for plastic waste detection and weight estimation. The system is able to perform multi-object detection within a single image, classify plastic waste types, and automatically estimate the weight of each object based on geometric features extracted from the detection results.

Overall, the system produces outputs in the form of plastic waste classes, number of detected objects, estimated weight per object, and total estimated weight within a single image. The object counting and weight aggregation process follows the defined object criteria, where each plastic component with its own measurable weight is counted independently. This demonstrates that the proposed approach is not only capable of performing visual detection but also supports quantitative analysis through regression-based weight estimation.

However, the weight estimation performance in this study is evaluated under controlled image acquisition conditions. Since the regression model relies on pixel-based geometric features extracted from bounding boxes, variations in camera distance, viewpoint, image resolution, and object scale may affect the prediction accuracy. Therefore, this study does not claim robustness against arbitrary camera distances or viewpoints. Future improvements may include camera calibration, depth information, or reference-scale objects to enhance generalization in uncontrolled environments. Additional experiments involving different camera distances and object orientations will be considered in future work to evaluate the robustness of the proposed approach under more diverse acquisition scenarios.

The end-to-end system architecture used in this study is illustrated in Figure 3, which shows the workflow from image input to final prediction output.

3.4 Comparison with Existing Studies

Comparison with previous studies shows that most approaches in plastic waste detection still focus on classification or object detection tasks, without involving quantitative estimation such as weight. In addition, several studies are still limited to single-object detection and have not fully utilized geometric information from bounding boxes for regression purposes.

The study by Hassadiqin and Utaminingrum (2023) used YOLOv5s for plastic waste classification based on the Resin Identification Code; however, the system was still limited to detection and did not provide quantitative estimation (Hassadiqin & Utaminingrum, 2023). Other studies have applied transfer learning-based CNN approaches for plastic waste classification, but they do not effectively support multi-object detection within a single image. Furthermore, CNN-based approaches generally produce only categorical outputs without the ability to predict continuous values such as weight (Faizal et al., 2023; Ginting et al., n.d.).

Based on these limitations, this study extends existing approaches by integrating YOLOv8n for multi-object detection and Random Forest Regression for weight estimation based on geometric bounding box features. This integration enables the system to produce not only qualitative outputs in the form of plastic waste categories but also quantitative outputs in the form of automatic weight estimation.

To clarify the differences in approach, Table 3 presents a comparison between this study and previous research.

Table 3. Comparison with previous studies.

Study	Method	Output	Limitation
Hassadiqin & Utaminingrum (2023)	YOLOv5s	Plastic waste classification	Limited to single-task detection, no weight estimation
Ginting et al. (Transfer Learning CNN)	CNN-based model	Plastic classification	No multi-object detection capability
Faizal et al. (Deep Learning Approach)	CNN	Waste identification	No regression or quantitative output
This Study	**YOLOv8n + Random Forest Regression**	**Multi-object detection + weight estimation**	**Sensitive to occlusion and lighting variation**

3.5 Summary of Findings

Overall, the results of this study indicate that:

a. YOLOv8n is effective in performing multi-class plastic waste detection and classification with high accuracy
b. Random Forest Regression is capable of estimating plastic waste weight with low error
c. The integration of both models produces an automated system capable of performing end-to-end detection and weight estimation
d. The bounding box feature-based approach is proven to be effective for image-based weight regression

However, since the weight estimation model relies on pixel-based geometric features extracted from bounding boxes, the prediction performance may be affected by variations in camera distance, object scale, viewpoint, and image acquisition conditions. Therefore, the current system is primarily designed for controlled image-capture scenarios. Future research should incorporate camera calibration, depth information, or scale references to improve robustness under varying environments.

4. Conclusions

This study successfully developed a computer vision-based system for plastic waste detection and weight estimation using a combination of YOLOv8n and Random Forest Regression models. The system is capable of detecting and classifying seven types of plastic waste, namely PET, HDPE, PVC, LDPE, PP, PS, and OTHER, with performance evaluated on an unseen test set achieving a mAP@0.5 of 91.93% and a mAP@0.5:0.95 of 73.27%. In addition, the Random Forest Regression model for weight estimation based on bounding box features achieves strong performance with an R^2 score of 95.5% and a Mean Absolute Error (MAE) of 4.28 grams. These results demonstrate that the integration of object detection and feature-based regression enables image-based plastic waste weight estimation, reducing the dependency on manual weighing processes under controlled image acquisition conditions. The proposed system also improves efficiency, speed, and objectivity in image-based plastic waste management. Furthermore, the current weight estimation approach is primarily validated under controlled image acquisition conditions. However, the system still has limitations under low lighting conditions, object occlusion, and complex variations in waste shapes. Therefore, future work is recommended to increase dataset diversity and improve model robustness to enhance performance in real-world scenarios.

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